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Prediction of Annual Flood-Prone Areas using SWAT and HEC-RAS Models

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Abstract

This study focuses on predicting flood-prone areas in Niger State's Kainji Lake watershed for 2025 using the SWAT and HEC-RAS models. The SWAT model replicates key hydrological processes, integrating satellite-derived data, including precipitation, temperature, land cover, DEM, and soil maps. HEC-RAS simulates river flow and flood inundation, utilizing a 12.5 m ALOS PALSAR DEM for detailed analysis. Both models are calibrated and validated with two years of discharge data from the Nigeria Hydrological Service Agency. Results highlight the vulnerability of several settlements along the Kainji Lake floodplain, such as Kontagora, New Busa, and Ngaski, under different climate scenarios. Despite certain limitations, the combined use of SWAT and HEC-RAS effectively identifies areas at risk in flood prediction and management efforts.

Keywords: Digital Elevation Model (DEM), Flood vulnerability, Hydrological data, Hydrologic Engineering Centre's River Analysis System (HEC-RAS), Soil and Water Assessment Tool (SWAT)

1. Introduction

Flood is one of the most catastrophic natural disasters globally (Adesina *et al.*, 2024). It is conceptualised as a situation that results when a part of the dry Earth's surface is covered with water due to a high amount of rainfall or the overflowing of a water body (Njoku *et al.*, 2013; Musa *et al.*, 2014; Aja *et al.*, 2019). The World Health Organization (WHO) reports that between 1998 and 2017, floods affected over two billion people globally (Shimelis *et al.*, 2016). Vulnerable populations living in floodplains, non-resistant structures, or lacking adequate warning systems and flood awareness are particularly at risk. Recent flood events across Europe, West and Central Africa, and Nigeria have highlighted the urgent need for adequate flood prediction and mitigation strategies (Nura and Alison, 2022; Sella *et al.*, 2022).

Floods have resulted in numerous fatalities and extensive damages all over the world. In 2020, over 1.3 million people in 13 countries across West and Central Africa were affected by flooding, with increased rainfall contributing to the severity of the impact compared to the previous year, according to the Internal Displacement Monitoring Centre (IDMC, 2021). In Nigeria, the 2012 floods caused the death of over 363 people and displaced approximately 2.1 million individuals, making it the worst flood in four decades, according to the National Emergency Management Agency (NEMA, 2020). The flood affected 30 out of 36 States, resulting in significant economic losses estimated at 2.6 trillion naira. In 2021, extreme flood events impacted all 36 states and the Federal Capital Territory in Nigeria, forcing over 2.3 million people to relocate and resulting in 69 deaths (Adesina *et al.*, 2023). Agricultural lands and houses were particularly devastated in Kebbi, Jigawa and Niger States (Nigeria Hydrological Service Agency - NIHSA, 2021).

Flood prediction is a complex process influenced by various factors, including spatial location, rainfall patterns, soil types, and catchment size (Odumosu *et al.*, 2014; Adesina *et al.*, 2022). However, it represents the most effective non-structural method for mitigating and managing floods. Compared to lumped hydrologic models, distributed hydrologic models such as SWAT can capture the heterogeneities in the river basin characteristics and hydrometeorological forcing (Agunbiade and Jimoh, 2013; Nguyen *et al.*, 2019). To facilitate effective flood prediction, a comprehensive analysis of time series data is crucial. Time series analysis involves examining a

sequence of data points collected over a specific time interval (Reynolds, 2019; Tableau, 2021; Adesina *et al.*, 2022). In flood prediction, this includes analysing daily flow records (stage and discharge) from hydrological stations (Zitta *et al.*, 2015; Abbaspour *et al.*, 2015), groundwater, and weather station data, as well as daily, monthly, and yearly rainfall records and potential evapotranspiration (PET) data.

Thus, the study aims to gather and analyse observed and remotely sensed data of the Kainji Lake watershed, which includes information on land use, soil type, rainfall, and river discharge. The goals are to calibrate and validate the SWAT model for the Kainji Lake watershed, use the calibrated model to predict the watershed's hydrological behaviour, simulate flood events using the HEC-RAS model, validate the results with observed data, and predict flood areas in Niger State for 2025, with a focus on the Kainji Lake.

The SWAT model was used to simulate hydrological processes while the HEC-RAS model was used to simulate river flow and flood inundation by incorporating satellite-derived inputs such as precipitation, temperature, land cover, DEM, and soil maps, and also calibrated and validated models using observed discharge data from NHSA. The results identified flood-prone areas along the Kainji Lake floodplain, including several settlements and predicted flood areas for 2025 under varying climate scenarios.

1.1 Study area

The study area, as pictured in Figure 1, is located at 9° 20'E - 10° 40'E longitude and 3° 40'N - 5° 20'N latitude of the Niger River. It lies on the border between Niger and Kebbi States in northwestern Nigeria. The area supports a significant population and is known for its agricultural activities, including farming and fishing, which contributes significantly to the local economy. The lake also supports hydropower generation, with the Kainji dam being a key source of electricity in Nigeria. Kainji Lake in Nigeria has a tropical climate with 800-1200 mm of annual rainfall concentrated in the wet season (May-October). The area's predominant soil types include sandy loam and clay loam. The topography features gentle undulations with elevations between 371 and 1266 feet. The local communities engage in different socioeconomic activities, including trading, livestock rearing, and small-scale industries. The Kainji Lake experienced periodic flooding, particularly during the rainy seasons. The lake wholly submerged Foge Island in the Niger River, the town of Bussa, and other riverine settlements while part of the old town of Yelwa (the seat of Yauri emirate) was also permanently flooded.

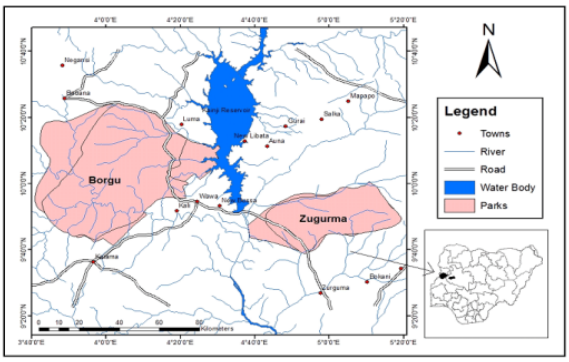


Figure 1: Study area map

2. Materials and Methods

2.1 Data collection

The data used for this study were sourced from secondary sources due to cost implications and limited access to observed hydro-meteorological input data in the study area. The collected data included a LandSat 8 used for land use/land cover (LULC) mapping, detailed Digital Elevation Model (DEM), soil map, weather data, and discharge. Satellite-derived Meteorological data from the Famine Early Warning Systems Network (FEWSNET) ranging from 2000 to 2019 were used in this study, including precipitation, minimum and maximum temperature, solar radiation, wind speed, and relative humidity. The data were recorded on a daily time step, and gauge locations for these variables were identified. Various data, such as land use, soil map, rainfall data, solar radiation, wind speed, and river discharge, were collected and analysed for the Kainji Lake watershed. ArcGIS 10.3 software was used to process the data into a format ingestible into SWAT and HEC-RAS models.

2.2 Hardware and software used

The following software was used for data collection, analysis, processing, and visualization: ArcGIS 10.3, ArcSWAT 2012, SWAT 2012, HEC-RAS 6.1, MWSWAT 2012, SWATCUP 2012, while the hardware used included a laptop (HP, Intel(R) Core (TM) i5-1005G1 CPU @ 1.20GHz 2.40 GHz processor, 8.00 GB RAM, 64-bit operating system, x64-based processor), and a printer.

2.3 SWAT model calibration and validation

Climate, topography, soil, land use, hydrology, and stream network datasets were used as input into the SWAT model. The simulated discharge data contain in the TxtInOut folder were calibrated and validated using the observed discharge for the Kainji lake watershed acquired from NIHSA. Model parameters such as: r_CN2.mgt, v_ALPHA_BF.gw, v_GW_DELAY.gw, v_GWQMN.gw, r_SOL_K.sol and r_TIMP.bsn were adjusted to match the observed river discharge data during the calibration process.

2.4 HEC-RAS model simulation

The HEC-RAS model was employed to simulate flood events in the Kainji Lake watershed using input data such as geometric data (river system layout and cross-sections), flow data (boundary conditions, flow hydrographs, lateral inflows), and Manning's roughness coefficients. The output from the SWAT model served as input to HEC-RAS and formed the basis for the hydraulic analysis. HEC-RAS creates a geometric representation of the river, including cross-sectional profiles and reaches. With user-defined parameters such as water surface profiles, flow discharges, and any proposed changes, HEC-RAS calculates the flow velocity and other hydraulic parameters, which were used to generate floodplain maps and delineate areas prone to flooding, displaying the results through the RAS mapper. While the complete set of equations used by HEC-RAS to make these simulations is extensive and highly technical, some fundamental equations that form the basis of its computations include:

Manning's equation: Equation (1) was used to calculate the flow velocity in an open channel based on channel characteristics and roughness coefficients (Nguyen *et al.,* 2019; Adesina *et al.,* 2022).

$$V = \frac{1}{n} R^{2/3} S^{1/2} \quad (1)$$

Where,

V is the flow velocity

n is Manning's roughness coefficient,

R is the hydraulic radius,

S is the channel slope.

Continuity equation: This represents the principle of mass conservation in fluid dynamics, starting with the fact that the flow rate at any point within an incompressible fluid system remains constant (Nguyen *et al.,* 2019; Adesina *et al.,* 2022).

$$Q = AV \quad (2)$$

Where,

Q is the flow rate,

A is the cross-sectional area of the flow,

V is the flow velocity.

The results from the HEC-RAS model were used to predict the flood areas in Niger State for the year 2025, with a specific focus on the Kainji Lake.

2.5 Models structure and simulations

The SWAT model is a small watershed to large river basin-scale model used for simulating groundwater and surface runoff that uses Hydrological Response Units (HRUs) to represent land use, soil, and slope characteristics within a watershed (Bounhieng *et al.,* 2015; Adegboyega *et al.,* 2018). The model simulates discharge using estimated hydrological components such as evapotranspiration, surface runoff, peak rate of runoff, groundwater flow, and sediment yield generated from the land use, soil map, and meteorological data ingested in it. ArcSWAT is a graphical user interface (GUI) for the SWAT model, integrated as an extension in ArcGIS 10.3. It allows a user to carry out simulations using the capabilities of the SWAT model within the ArcGIS environment.

SWAT Calibration and Uncertainty Program (SWAT-CUP) is a software developed for calibrating the SWAT model. The Software was developed by the Swiss Federal Institute of Aquatic Science and Technology for calibrating the SWAT model. In SWAT-CUP software, five algorithms can be selected for parameter verification, namely the SUFI2 algorithm, GLUE Algorithm, Parasol algorithm, MCMC algorithm, and PSO algorithm. The SUFI2 algorithm has the fastest operation process and high accuracy (Zhang, 2016) and is therefore used in this research to optimise the accuracy of the result.

3. Result and Discussion

3.1 Digital Elevation Model (DEM)

The SRTM 30 m resolution and ALOS PALSAR 12.5 m DEMs were obtained from the United States Geological Survey (USGS) and Alaska Satellite Facility (ASF), respectively. The acquired DEMs covered the entire Niger State from which the tiles covering the study area were sub-mapped and mosaic together to create a smooth continuous mask surface of the area as shown in Figure 2. The choice of selecting different DEM for each model was due to the watershed size and the sensitivity to one-dimensional and two-dimensional simulations in HEC-RAS. The DEM exhibited high accuracy across most parts of the analysed basin. However, its accuracy declined in certain regions, like urban and riverside zones, attributed to the visual properties of developed regions.

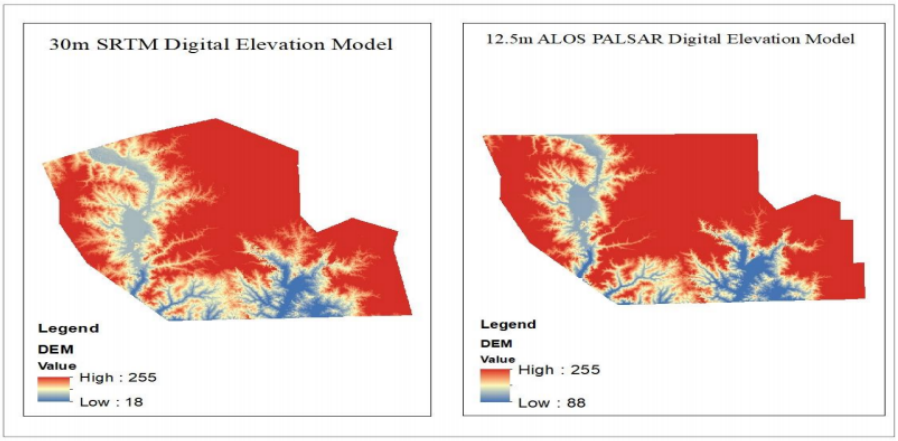


Figure 2: DEMs of the Kainji watershed (earthexplorer.usgs.gov/asf.alaska.edu)

3.2 Watershed

The watershed was modelled using a monthly time step of the weather data, which means that the hydrologic processes and water flows are calculated every month as a summation of daily precipitation, temperature, wind, and solar radiation. It allows for a more detailed analysis of how water moves through the system and how it is affected by seasonal changes in weather and land use. The watershed in this study covers about 26,125 Km², 111 Hydrologic Response Units (HRUs), and 32 sub-basins, as shown in Figure 3. Overall, the watershed is a complex and dynamic system that requires careful management and planning to ensure that it can provide the necessary water resources for human and environmental needs while also protecting the health and integrity of the ecosystem.

3.3 SWAT model simulation

The SWAT model brings together all the hydro-meteorological parameters to form a single overlay that defines the hydrologic system of the watershed. Some apparent objects identified on the map are DEM, HRUs, Monitoring points, basins, reaches, and Reservoirs, as presented in Figure 4.

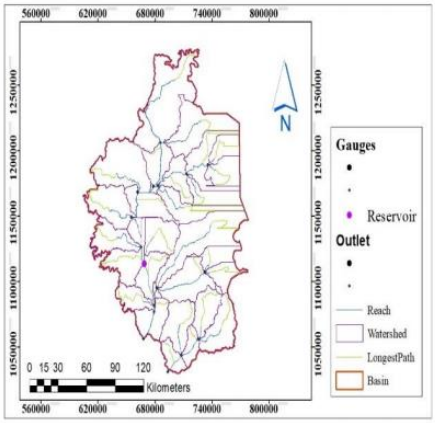


Figure 3: Delineated watershed containing Kainji lake

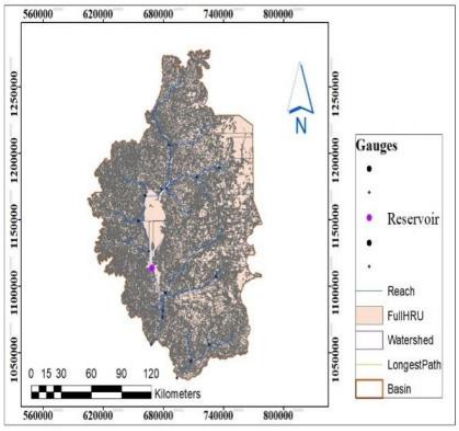


Figure 4: Kainji watershed hydro-meteorological system

Figure 5 depicts how the predicted discharge (Q2) values (23 values) behave with the observed discharge values (Q1) (23 observations). In general, SWAT predictions were relatively close to the observed values in terms of the trends. However, SWAT showed some decrease corresponding to slight variations in the observed values due to the large area of the covered watershed. These differences were considered when calibrating the model for final prediction.

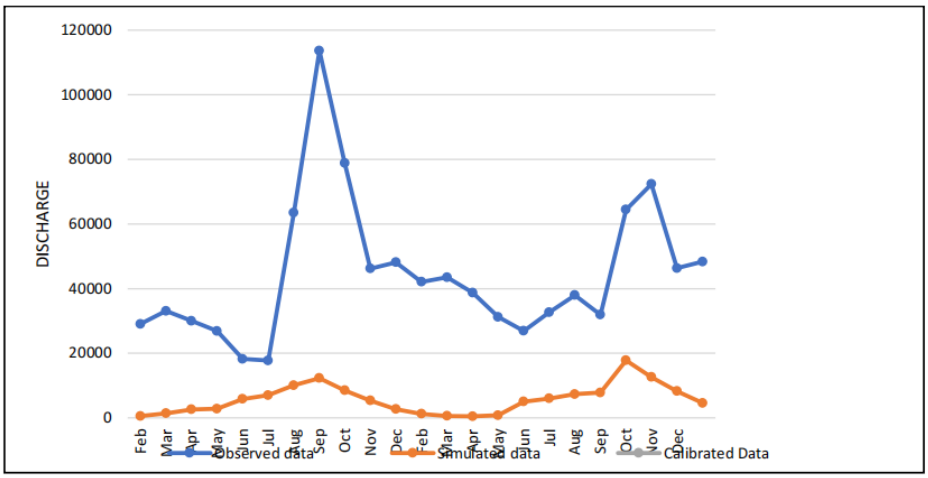


Figure 5: Comparison between observed and simulated discharge

3.4 Model calibration and validation

The performance of the SWAT hydrologic model was evaluated using historical daily discharge data over a 4-year period from 2018 to 2022. The performance of SWAT was excellent in estimating discharge values as demonstrated by the statistical measures, including coefficient of determination (R^2) of 1 and Nash-Sutcliffe index (NSI) of 1 percent, which indicates a slight underestimation of the simulated values. The model performance was evaluated for a two-year validation period (2020-2022). Subsequently, the statistical indices for the validation period showed that the model performance was as good as for the calibration period with statistics as listed in Table 1.

Table 1: Summary of statistics of best estimation

Variable	p-factor	r-factor	R^2	NSI	bR^2	MAP	SSQR
FLOW_OUT_27	1	0.76	1	1	0.9903	790	650
FLOW_OUT_27	PBIA	KGE	RSR	MNS	VOL_FR	μ O/S	σ^2 O/S
FLOW_OUT_27	-0.1	0.99	0.04	0.96	1	795.70/795.02	645.71/640.04
FLOW_OUT_27	p-factor	r-factor	R^2	NSI	bR^2	MAP	SSQR
FLOW_OUT_27	1	0.76	1	1	0.9903	790	650
FLOW_OUT_27	PBIA	KGE	RSR	MNS	VOL_FR	μ O/S	σ^2 O/S
FLOW_OUT_27	-0.1	0.99	0.04	0.00	1.00	795.70/795.02	645.71/640.04

The scatter plots of parameter values versus the objective function, as shown in Figure 6, illustrate the distribution of the sampling points utilised in the validation process. These statistics are generally employed to compare observed data with the simulation range. The best simulation for the current iteration is calculated and used for post-processing (prediction).

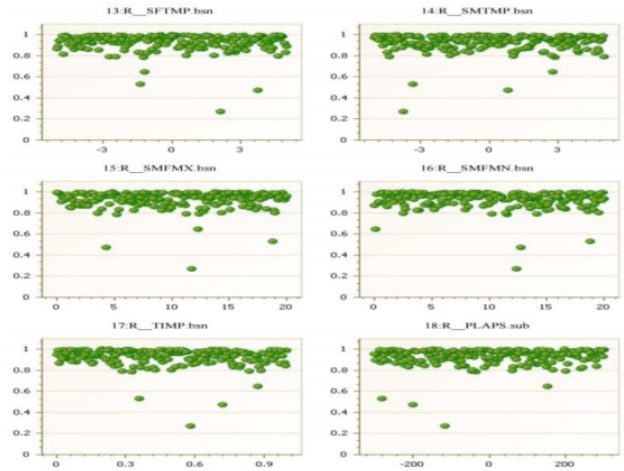


Figure 6: The dotty plots of parameter values versus objective function

The variable FLOW_OUT_27 represents the sub-basin containing the lake (Kainji) in the watershed that was calibrated with 24-month observation data. The calibration and validation lasted 30 minutes, using 20 parameters in 200 simulations. Figure 7 illustrates the calibration and validation of the model with 95% prediction uncertainty.

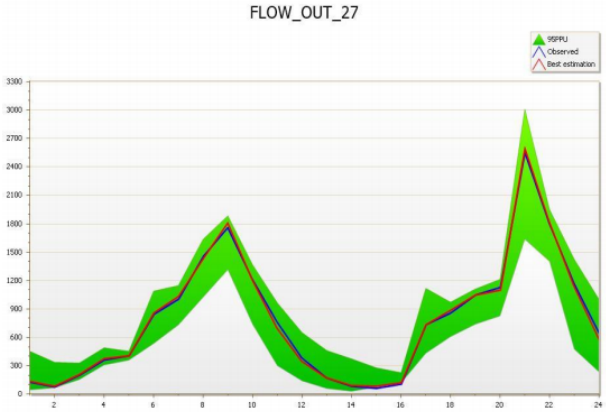


Figure 7: The 95% prediction uncertainty of the observed against best estimate

3.5 HEC-RAS simulation

The best estimates computed from SWAT are inputted into HEC_RAS as hydrographs; these observations represent the flow hydrograph of the two-dimensional unsteady flow simulation, as shown in Figure 8. The HEC-RAS hydraulic model was applied with an hourly time step using SWAT model results as the upstream boundary condition. In the downstream, however, average depths are applied with a friction slope of 0.05 m. The friction slope is based on the land slope of the area boundary condition line vicinity.

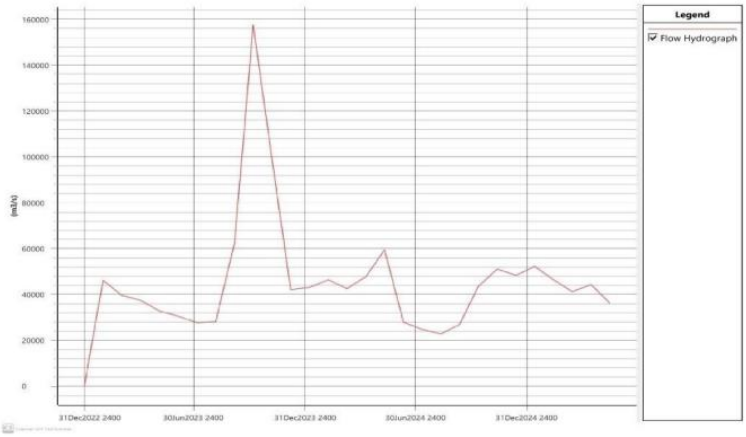


Figure 8: Two-year simulated flow hydrograph (2023-2025)

The simulation shows the inundation of several neighbouring towns, including some parts of Kontagora, New Busa, Tungan Maishagali, Shagurnnu, Wawu, Ngaski, Azarunji, and New Libata, as shown in Figures 9 and 10, respectively.

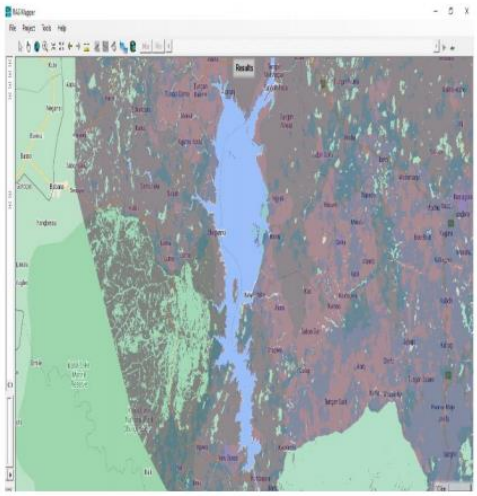


Figure 9: HEC-RAS simulation before inundation

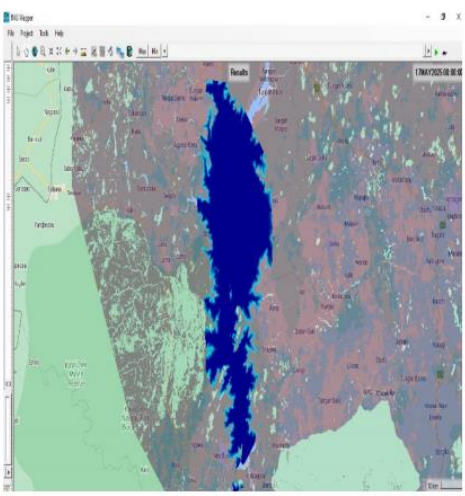


Figure 10: HEC-RAS simulation after inundation

4. Conclusions

This study predicts and simulates flood inundation in the Kainji watershed but can be used for any watershed within Niger State if the DEM, soil map, landcover map, and precipitation of the location are ingested into the SWAT model and HEC-RAS. The capacity that the SWAT model showed in this study highlighted the visibility of using remotely sensed hydro-meteorological data to analyse the behaviour of any hydrological system, even though the accuracy is greatly improved within a relatively small watershed. The study provides valuable insights into the hydrological behaviour of the watershed, such as flow depth, velocity during flood events, water surface elevation, and inundation boundary. Based on the best estimation of the model, in 2025, from February to May, the highest outflow of about 52,383 m^3/s will be observed, which may lead to the flooding of some parts of Kontagora, New Busa, Tungan Maishagali, Shagurnnu, Wawu, Ngaski, Azarunji and New Libata. The study outcomes will be helpful for policy-

makers and decision-makers to implement measures to reduce the damage caused by flood trials or of the watershed during flood events and the impact of land use changes and climate change on floods. Due to inadequate validation data, this study could only make a short-time prediction. It is recommended that by following the steps and methodology provided in this study, SWAT can be used with adequate validation data to make a more accurate flood prediction with a relatively extended forecast period. However, it is essential to note that SWAT has certain limitations and uncertainties, and the predicted results should be interpreted with caution.

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